

# A Multi-Dimensional Customer Segmentation Model Using The Fuzzy C-Means Clustering Algorithm: A Pilot Study In The B2B Setting

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## Abstract

*Customer segmentation allows companies to create mutual profiles of their customers. Determining industrial customer segments based on a single perspective causes various customer features to be disregarded. This study aims to develop a holistic segmentation approach in a B2B setting. The paper proposes a multi-dimensional segmentation model with four main criteria: customer purchasing performance, customer cooperation, customer workload, and customer potential. The case study demonstrates the real-life application of the proposed model using 379 customer data and 17 sub-criteria under four dimensions. The Fuzzy C-Means Clustering Algorithm creates the customer segments, and the Fuzzy Analytical Hierarchical Process is used to calculate criteria weights. The marketing strategies of each segment are used to guide customer relations and managerial decisions. This paper suggests that companies segment their customers by considering financial performance, cooperation level, future potential throughput, and challenges. It provides a practical and holistic insight into industrial customer segmentation.*

**Keywords:** *Customer segmentation, industrial customer relations, fuzzy analytic hierarchy process, fuzzy C-means algorithm*

**JEL Code:** *M31, C38, D81*

<sup>1</sup> This article is based on the author's dissertation.

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## Bulanık C-Ortalamlar Kümeleme Algoritmasını Kullanan Çok Boyutlu Bir Müşteri Segmentasyon Modeli: B2B Ortamında Bir Pilot Çalışma

### Öz

Müşteri segmentasyonu, işletmelerin müşterilerinin ortak profillerini oluşturmalarına olanak tanır. Endüstriyel müşteri segmentlerinin tek bir bakış açısına göre belirlenmesi, çeşitli müşteri özelliklerinin göz ardı edilmesine neden olmaktadır. Bu çalışma, B2B ortamında bütünsel bir segmentasyon yaklaşımı geliştirmeyi amaçlamaktadır. Çalışmada dört ana kriter içeren çok boyutlu bir segmentasyon modeli önerilmektedir: müşteri satın alma performansı, müşteri işbirliği, müşteri iş yükü ve müşteri potansiyeli. Vaka çalışması, 379 müşteri verisi ve dört boyut altında 17 alt kriter kullanarak önerilen modelin gerçek hayattaki uygulamasını göstermektedir. Bulanık C-Ortalamlar Kümeleme Algoritması müşteri segmentlerini oluşturmakta ve kriter ağırlıklarını hesaplamak için Bulanık Analitik Hiyerarşik Süreç kullanılmaktadır. Her bir segmentin pazarlama stratejileri, müşteri ilişkilerini ve yönetimsel kararları yönlendirmek için kullanılır. Bu çalışma, işletmelerin finansal performans, işbirliği düzeyi, gelecekteki potansiyel iş hacmi ve zorlukları dikkate alarak müşterilerini segmentlere ayırmaları gerektiğini öne sürmektedir. Endüstriyel müşteri segmentasyonuna pratik ve bütüncül bir bakış açısı sağlamaktadır.

**Anahtar Kelimeler:** Müşteri segmentasyonu, endüstriyel müşteri ilişkileri, bulanık analitik hiyerarşik süreci, bulanık C-means algoritması

**JEL Kodu:** M31, C38, D81

## Introduction

Customer relationship management (CRM) helps in making strategic decisions by selecting the most profitable customers and shaping the interactions with those customers (Kumar, 2010). Profitability is generally addressed with monetary value according to the past transactions of the customers and future predictions. However, the indirect contributions of the customers for potential profitability are ignored. Apart from financial returns, strong relationships with industrial customers enable a company to obtain more accurate demand forecasts (Fiala, 2005; Min et al., 2019; Özkan & Ward, 2020), to increase its business volume by developing new ideas and products with joint R&D projects (Bonner & Walker, 2004; Zander & Zander, 2005; Noordhoff et al., 2011; Zheng et al., 2022), to obtain new customers with customer references (Johnson et al. 1997; Ma et al. 2011) and to maintain its market position through the development of loyal customers. The multi-dimensional approach provides to evaluate industrial customers for marketing expenditures and customizing offerings for them in the Business-To-Business (B2B) settings.

Within the scope of analytical CRM, customer segmentation (Smith, 1956) simplifies the complexity of dealing with large numbers of individual customers, each with their own distinct needs, purchasing attitudes and behaviors, and different potential values (Sota et al., 2018; Wilson et al., 2002; Kotler & Armstrong, 2012; Bošnjak & Grljevi, 2011). Customer segmentation takes an entire customer population or a subgroup of this population and clusters them into homogeneous groups based on their preferences, characteristics, and values (Liozu & Hinterhuber, 2019). And segmentation is used to define and increase the value of their industrial customers (Ritter & Andersen, 2014). Traditional segmentation techniques are limited by their focus on single criteria, leading to the omission of critical customer characteristics (Hadad & Keren, 2022). Recent studies highlight the importance of multi-dimensional segmentation models that consider multiple factors (Pradana & Ha, 2021). However, the determination of the segmentation dimensions for customer clustering is another tough decision for executives.

The customer segmentation variables generally depend on customer behavioral characteristics, especially those pertaining to customer purchases and value-oriented attributes (Hiziroglu, 2013). Customer lifetime value (CLV), as value-oriented attributes identified the financial gain derived from customers over their lifetime of transactions, is aimed at shedding light on strategic CRM decisions that utilize profitability measurement from several approaches (Bayer, 2010; Payne & Frow, 2005; Chan, 2008; Simkin, 2008). Value-based segmentation regarding CLV estimates depends on using parameters depending on customer behavior (Hwang et al., 2004; Gupta et al., 2006). Hiziroglu and Sengul (2012) categorize the models used to calculate CLV into two groups, models for past customer behavior and models for future-past customer behavior. The RFM model (recency-frequency-monetary), which is one of the most widely used models and works based on past customer behavior, portrays customer monetary behavior and allows companies to determine which customers are worth communicating with (Gupta et al., 2006; Wei et al., 2010). The RFM model predicts purchasing behavior by using when, how often, and in what quantity customers have previously purchased (Yan et al., 2018). The basic assumption of RFM is that a customer's future behavior is based on their past and present behavioral patterns. Similarly, the PCV model is used to examine the total contribution to the current profits based on all previous transactions. The SOW model is used to calculate the amount of money that customers regularly allocate to a particular brand/company rather than to competing brands in the same product category. Future-past behavior-based models are generally used to calculate CLV both with and without customer acquisition cost with mathematical formulas (Hwang et al., 2004; Gupta et al., 2006; Berger & Nasr, 1998; Gupta & Lehman, 2003). The measures of CLV and customer segmentation are not based on a precise model because of the difficulties in predicting customer behavior (Singh et al., 2009; Ekergil & Ersoy, 2016).

Customer segmentation dimensions change according to sector, company, and customer profile, and different calculations can be developed for each company depending on their internal processes and priorities (Wind, 1978; Kumar et al., 2004; Tsiptsis & Chorianopoulos, 2009; Jayaratne et al., 2017). Companies might prefer to use a single variable, a few specific variables, or a combination of single and multiple variables for customer segmentation. Kolarovszki, Tengler and Majerčáková (2016) developed a three-dimensional segmentation model for postal enterprise customers that consists of the development potential, cost to serve and relationship value of customers. Cooil, Aksoy and Keiningham (2008)

determined behavioral dimensions in the retail sector, including the amount spent, purchasing type, food and nonfood purchased, seasonality, basket size, and communication degree. In their segmentation model, Kim, Fong, and Desarbo (2012) concentrated on customer perceptions of quality based on independent variables such as region, account type, business type, relationships with other suppliers, the number of employees of the company, and the number of years as a customer. Bayer (2010) determined segmentation variables regarding speaking time, frequency, and amount spent in the example they gave for the telecommunications sector. Casas-Rosal et al. (2021) explored the use of multi-criteria decision-making approaches to segment food markets based on consumer preferences. Their research highlights the effectiveness of multi-criteria methodologies in developing actionable customer groups. Similarly, Kim and Lee (2023) proposed a multi-criteria customer segmentation model integrating sentiment analysis with clustering techniques to capture both quantitative and qualitative customer attributes. For industrial customer segmentation, while some studies involve industrial customer segmentation by using RFM parameters (Kumar & Philip, 2022; Maulina et al., 2019; Ramkumar et al., 2025), Nairn and Berthon (2003) stated that the general segment criteria have changed from demographic, geographic, and purchasing volume to brand preferences, repeat purchases, or profitability metrics. Tsiptsis and Chorianopoulos (2009) defined industrial customer segmentation variables as value, size, industry type, and company life stage. On the other hand, Güçdemir and Selim (2015) proposed five industrial customer segmentation variables: loyalty, average annual demand percentage, long-term relationship potential, and percentage of change in average annual sales revenues. Sheikh, Ghanbarpour and Gholamiangonabadi (2019) used purchasing length, recency, frequency, monetary and periodicity dimensions for the B2B setting. Barrera et al. (2024) developed a multicriteria model to support decision making for customer segmentation in a B2B context by using variables such as RFM, customer collaboration and growth rates.

In B2B contexts, effective customer segmentation is pivotal for tailoring marketing strategies and optimizing resource allocation. In addition to the financial segmentation dimensions intensively studied in the literature mentioned above, distinctive characteristics arising from industrial customers' relationships with the business should also be considered. It is well recognized that for an effective supply chain management players need to collaborate and align their operations, while also participating in joint, mutually agreed-upon decision-making processes (Wendel et al., 2013; Galli et al., 2021). Coordinating partners to achieve shared goals is essential for fostering a successful and mutually beneficial exchange relationship and cooperating with customers is vital to value creation and increase the service innovations (Mention, 2011; Limpanitgul et al., 2013; Marcovic et al., 2020; Virtanen & Björk, 2024). Therefore, companies benefit more from customers with whom they have a high level of cooperation. While the degree of cooperation differentiates customers, workload is another factor that influences this balance. The difficulty of some customers' demands or the complexity of the nature of the work to be done creates a burden on the relationship with those customers. In addition, increasing consumer expectations for enhanced services, complex products, longer product warranties, and evolving sustainability regulations bring novel challenges to producers (Kreye & van Donk, 2021; Menon et al., 2024). Another vital factor for long-term customer relationship planning is assessing a customer's potential growth and alignment with the company's strategic objectives. Ignoring a customer's potential because their current spending is low is a shallow perspective. Because customers often distribute their expenditure among several firms. They may possess greater overall spending capacity and could increase their spending with the company if competition decreases or the company offers improved products or services (Hanneke et al., 2024). As a result, these factors, other than the direct monetary relationship between industrial enterprises, show that different customers may have different effects on the company. To the best of the author's knowledge, no empirical studies have been published as of now which detail how to develop a segmentation model for considering customer purchasing performance, customer cooperation, customer workload, and customer potential factors simultaneously.

This study seeks to answer how a holistic, multi-criterial segmentation model can be developed and applied to industrial customers to improve strategic decision-making and customer relationship management. And it aims to propose a holistic segmentation model tailored to industrial customers, incorporating multiple dimensions such as financial performance, cooperation levels, workload, and potential growth. While the model examines customers in four main dimensions, it recommends that companies create sub-criteria in line with their own needs.

## A holistic customer segmentation model

This study proposes a holistic segmentation model that covers the financial performance of industrial customers, their collaborative method of doing business with the company, their corporate difficulties, and their future business potential.

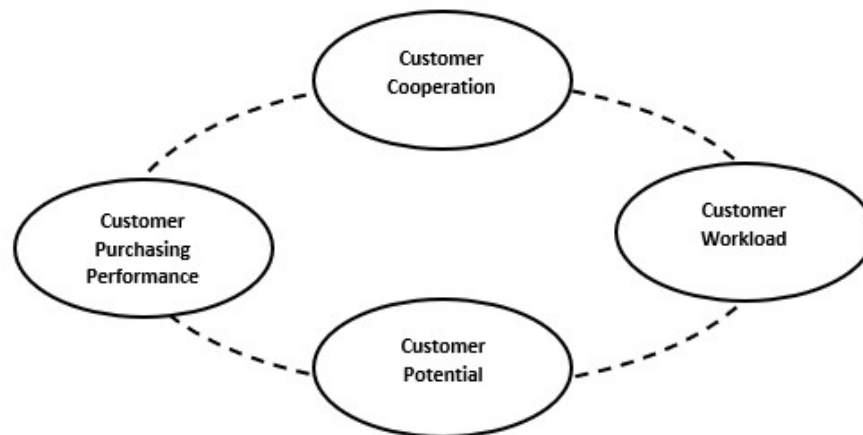


Figure 1. The holistic customer segmentation model( Created by the author).

The model demonstrated in Figure 1 is focused on the different dimensions of the relationship between companies and their customers, including such dimensions as "customer purchasing performance," "customer cooperation," "customer workload," and "customer potential." The customer purchasing behavior and the financial results under customer purchasing performance reveal customer characteristics from a monetary perspective. The indicators of this dimension are generally critical for companies due to profitability concerns. Customer cooperation is an important aspect of the customer experience and the perceived quality of products and services. The strength of the relationship causes the customer to be more willing to pursue joint gains in conjunction with the company. As good relations increase the level of cooperation, cooperation also supports relationships and connects customers to the company. Customer cooperation has many indicators, such as knowledge sharing, joint product development, participation, and loyalty. On the other hand, customer workload emerges in the relationship as a burden placed on the company by the customer. Companies that try to meet the demands of their customers also exert power at each step of service delivery. Along with notional forces, such purchasing persuasion, information sharing, and price negotiation, such companies encounter tangible forces such as the necessity of providing the necessary people, machines, and materials to produce customer orders. Last, criteria such as the levels of investment and progress made and the capacity of the customer within the company sector are indicators that reveal the potential of doing future business with the customer. Companies can divide their customers into segments by creating sub-criteria from the four proposed criteria aligned with their needs. The case study illustrates a real-life application of the proposed model.

### An application in the B2B setting

The case company is a leading reducer manufacturer in the industrial machinery manufacturing sector. It focuses solely on B2B markets in construction, mining, food, agriculture, livestock, textiles, air conditioning, and transportation systems. Its portfolio encompasses three customer types: dealers, machine manufacturers, and end-user companies. The data set used in this case study covers the transaction details of 379 dealers for three years. These are customers with whom relationships are relatively high and transactional data recording is more detailed.

This study employed the in-depth interview technique, a commonly used qualitative research method, to gather detailed insights into customer segmentation. The exploratory research process involved multiple stages to ensure a comprehensive understanding of customer behaviors and perceptions. In the first stage, preparatory work was conducted to design the interview questions. These questions were developed based on the four main criteria of the segmentation model: customer purchasing performance, customer

cooperation, customer workload, and customer potential. The questions were semi-structured to allow flexibility and to capture in-depth perspectives from the participants. Relevant literature was also reviewed to ensure the questions were aligned with established segmentation principles. Interviews were conducted with the marketing manager of the business, who provided a strategic perspective on customer segmentation. Additionally, three employees from the sales and marketing team were interviewed to offer operational insights and firsthand experience with customers. These participants were chosen for their direct involvement in customer interactions and their understanding of both the quantitative and qualitative aspects of customer relationships. The data collection phase involved conducting interviews over four full days. Each interview lasted between 60 to 90 minutes, depending on the depth of the discussion. The sessions were recorded with participant consent and were used for analysis. Participants were encouraged to provide examples and elaborate on their experiences to capture nuanced perspectives. During the analysis phase, the interview data was systematically reviewed using thematic analysis. Responses were categorized and coded according to the main criteria of the segmentation model. Through this process, both the positive and negative aspects of customers were identified. To enhance research transparency and reliability, the findings were discussed in a debriefing session with the participants, enabling further clarification and validation. Additionally, any discrepancies or differing viewpoints were carefully examined to provide a balanced and objective interpretation of the data. Overall, this rigorous and multi-stage approach ensured a robust understanding of customer characteristics. By triangulating insights from various participants and systematically analyzing the data, the study offers well-rounded conclusions that contribute to the refinement of the segmentation model. As a result, 17 criteria were specified under the proposed customer segmentation model, and Figure 2 shows the company's segmentation criteria. Under the customer purchasing performance criterion, gross profitability, purchase amount, payment terms, order frequency, sales revenue, and discount rate take part. Demand forecast accuracy is measured through the ratio of declared and occurrence, the acquisition of new customers through customer recommendations, the relevant number of joint R&D projects initiated and the degree of loyalty, in conjunction with customer cooperation. Difficulty with the supply of raw materials, production difficulties concerning customer orders and special product requests are the primary customer difficulties. The number of brands in the dealer's portfolio, total customer revenue, the number of competitors in its region, and the number of regions in which customers are served all serve as the criteria for customer performance. All sub-criteria apart from loyalty degree, difficulty with raw material supply, and difficulty in production are obtained from the company's ERP system. The marketing department categorizes the loyalty degree, material supply difficulty, and production difficulty according to their insights and knowledge. Additionally, the discount rate, the difficulty of raw material supply, difficulty in production, special product requests, and the number of competitors in the customer region are negative dimensions used in the evaluation of customers.

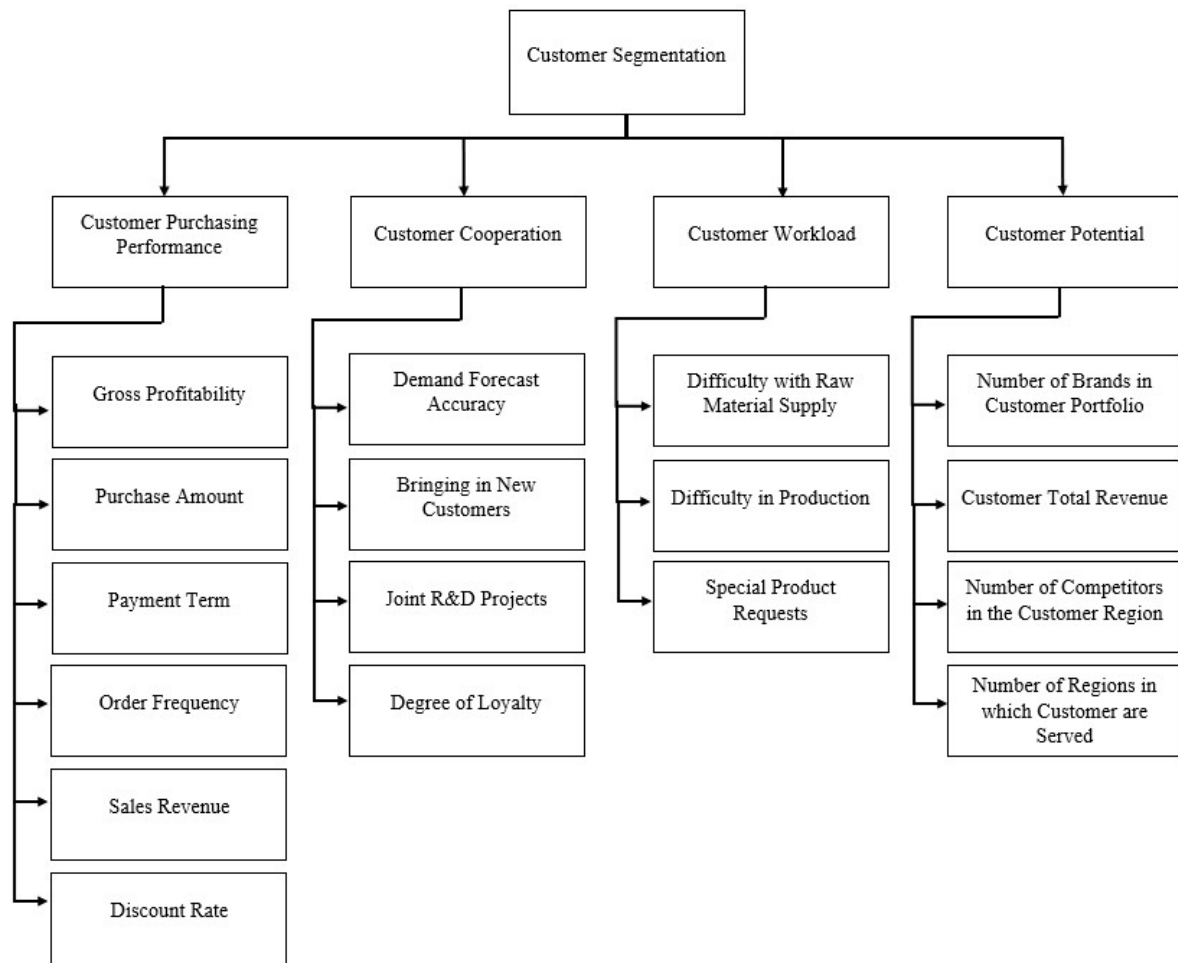


Figure 2. The detailed customer segmentation model of the case company( Created by the author).

### Calculation of segmentation criteria weights using fuzzy AHP

The perspectives of different evaluators and the variability of language as processed by subjective perceptions both affect the determination of the relevant criteria. Multicriteria decision-making (MCDM) method is used to detail how decision-makers evaluate the available alternatives and choose the best solution (Wang & Lee, 2009). The Fuzzy Analytic Hierarchy Process (Fuzzy AHP), one of the most popular MCDM techniques, is used to represent human thoughts, facilitate the processing of qualitative and quantitative information, apply hierarchical structure, reduce pairwise comparisons, and create priority vectors (Ibrahim et al., 2011).

The Fuzzy AHP method was used to calculate the weights of the upper criteria and the sub-criteria decided by the marketing department. The segmentation criteria weights are calculated according to the fuzzy AHP through the geometric mean method (Buckley, 1985). The main criteria are compared through a fuzzy scale by constructing a pairwise comparison matrix, and the sub-criteria under each main criterion are compared with each other. Fuzzy geometric mean values ( $\tilde{r}_i$ ) of the criteria (j) are calculated for all (i) by multiplying fuzzy numbers. The fuzzy criterion weights ( $\tilde{w}_i$ ) are equal to the normalization of the fuzzy geometric mean values, as given in the formula below.

$$\tilde{r}_i = (\tilde{M}_{i1} \otimes \dots \otimes \tilde{M}_{ij})^{1/j}$$

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \dots \oplus \tilde{r}_j)^{-1}$$

According to the results of the main criteria weights, customer purchasing performance ( $\tilde{w}_1$ ) has the highest weight at.662. The customer cooperation criterion ( $\tilde{w}_2$ ) comes next with a ratio of 0.179, and the customer workload criterion ( $\tilde{w}_3$ ) ranks number three with a weight of 0.102. Finally, the criterion weight of the customer potential ( $\tilde{w}_4$ ) is 0.057.

I calculate the individual effects of sub-criteria by multiplying the weights of each sub criterion and the weights of their main criteria, as shown in Table 1. These values are used to determine the importance levels of the segments after running the clustering algorithm.

Table 1

Segmentation Criteria Weights

Customer Performance	Purchasing	Customer Cooperation	Customer Workload	Customer Potential			
Gross Profitability	.173	Demand Forecast Accuracy	.021	Difficulty with Raw Material Supply	.042	Number of Brands in Customer Portfolio	.008
Purchase Amount	.195	Acquiring New Customers for The Company	.045	Difficulty in Production	.042	Customer Total Revenue	.030
Payment Term	.107	Joint R&D Projects	.015	Special Product Requests	.018	Number of Competitors in the Customer Region	.013
Order Frequency	.024	Degree of Loyalty	.098			Number of Regions in which Customer are Served	.007
Sales Revenue	.064						
Discount Rate	.098						

### Customer segmentation process using the fuzzy C-means clustering algorithm

There are many segmentation techniques, such as clustering, classification, evolutionary algorithms, self-organizing maps, and artificial neural networks, for creating similar customer groups. Fuzzy clustering is a partitioning cluster algorithm that divides an entity set into several homogeneous clusters according to the chosen similarity measure. The fuzzy C-means method (Dunn, 1974; Bezdek, 1981), one of the most well-known fuzzy clustering algorithms, is used to determine membership functions based on a distance function and calculate membership degrees according to the proximity of entities to the cluster centers. The algorithm works as follows (Havens et al. 2012)

1. Initialize the partition matrix  $U = [u_{ij}]$
2. Calculate the center vector  $C$  for each step.

$$C_i = \frac{\sum_{j=1}^n u_{ij}^m x_j}{\sum_{j=1}^n u_{ij}^m}$$

3. Calculate the distance matrix.

$$d_{ij} = \sqrt{\sum_{i=1}^n x_i - c_i}$$

4. Update the partition matrix.

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left[ \frac{d_{ij}}{d_{kj}} \right]^{2/(m-1)}}$$

5. If  $\|U(k+1) - U(k)\| < \epsilon$ , then end the algorithm; otherwise, return to step 2.

Determining the ideal number of clusters is a general problem for fuzzy methods due to the lack of prior knowledge (Zanaty, 2012). The exact number of clusters should be calculated to determine the maximum resemblance in each class generated. To determine the number of clusters, the elbow method is used to provide an optimal number of clusters by SSE (sum of square error), and the silhouette index is used to measure the effectiveness of the generated clusters by measuring the inter- and intra-cluster distances of the generated clusters (Marutho et al., 2018; Sharma et al., 2017; Waheed et al., 2020).

I coded the fuzzy C-means clustering algorithm with 379 customers and 17 segmentation criteria using Visual Basic Applications (VBA). All runs were made on a PC with an Intel® Core™ I5-3360 M CPU@2.80 GHz and 8.00 GB RAM. Table 2 shows the silhouette index (SSE), number of iterations, and process time according to the increased number of clusters.

Table 2

Number of Clusters and Related Indicators

Number of Clusters	SSE	Silhouette Index	Number of Iterations	CPU Time (sec.)
2	.148	.863	29	62.14
3	.125	.717	66	90.66
4	.127	.510	44	87.66
5	.130	.492	26	77.25
6	.128	.489	12	64.23
7	.126	.509	14	69.08
8	.126	.428	16	76.37
9	.124	.525	13	72.69
10	.123	.448	20	90.82

Figure 3 displays the changes in SSE values based on the number of clusters. According to the elbow method, the elbow of the SSE curve occurs when the number of clusters reaches 3. Since there is a further decrease in the silhouette index after the third cluster, as seen in Table 2, the number of clusters is determined to be 3.



Figure 3. SSE and the number of clusters

The number of customers assigned to these three clusters and their membership degree statistics are given in Table 3.

Table 3

Number of Customers in the Clusters and their Membership Degrees

Clusters	Num. of Customers	Avg. Degree of Membership	Max. Degree of Membership	Min. Degree of Membership
1	341	.950	.989	.701
2	28	.675	.847	.392
3	10	.852	.965	.475

The average membership degree of the customers in each cluster is above 50%. The highest membership degrees, which can be seen in Cluster 1, indicates the grouping of many customers with similar characteristics. The elements with the minimum membership degrees, which are grouped in Cluster 2, differ from their general customer profiles and can be defined as discrete elements.

### Marketing strategies for customer segments

Defining the customer segments with common customer characteristics facilitates the development of marketing strategies. The profile features of the segments are given in Figure 4 according to the distribution of center segment coordinates revealed through the consideration of 17 segmentation criteria. There is a clear difference between the three segments included in "customer purchasing performance", and the "degree of loyalty" as derived from "customer cooperation" is distinctive. "Special product requests" stand out in the "customer workload", while "customer total revenue" plays a distinctive role in the "customer potential" criterion.

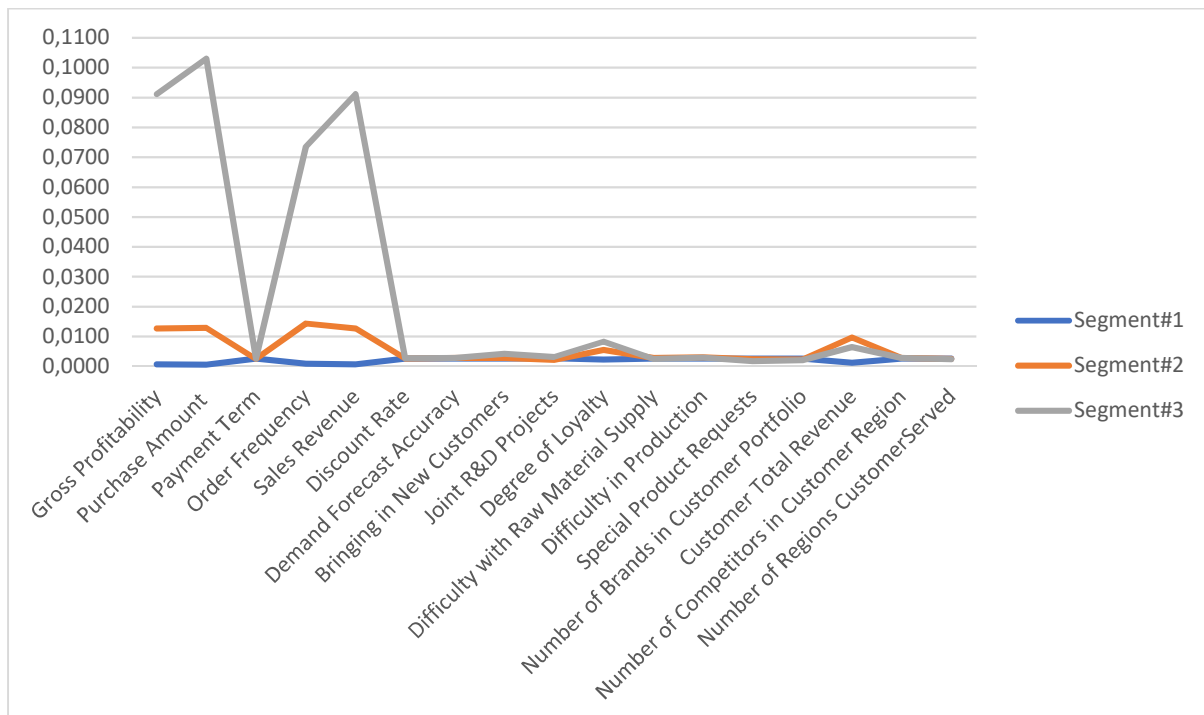


Figure 4. Distribution of the center of segment criteria

The customer data shown in the first segment, which is the most crowded segment, reveal that the first segmentation criterion values, "customer purchasing performance," are generally lower than those of the other two segments. The fact that the value of the "payment term" is the highest among them, even with just a tiny difference, creates a negative indicator for this segment. This segment is in the last place when ranking "demand forecast accuracy," "customer converted from competitors" and "loyalty degree" as related to "customer cooperation". Under the "customer workload" criterion, "manufacturing difficulty" is positively differentiated from other segments, while "special product demand" has the highest rates, thus describing a negative effect. In the last criterion, "customer potential," the sub-criteria values of "number of brands in the customer portfolio" and "number of regions served" are higher than other segments. The "customer total revenue" data fall significantly behind in the other two segments. Overall, the first segment's customer profile has low purchasing performance and cooperation but shows midrange levels for customer workload and potential.

The second segment data, apart from the "payment term" sub-criterion, has average values in all the sub-criteria of "customer purchasing performance". While "joint R&D projects" has the lowest value in the "customer collaboration" criterion, it exhibits a moderate profile in other sub-criteria. According to the "difficulty with raw material supply" and "difficulty in production" sub-criteria under "customer workload", the most difficult customers are categorized in this segment. These customers are in first place in the "customer total revenue" sub-criterion regarding "customer potential," and they exhibit a significant difference compared to customers in other segments. In general, customers in the second segment exhibit average performance and cooperation, high customer workload, and high customer potential in their relationship with the company.

According to the data of the third segment, the "payment term" sub-criterion under "customer purchasing performance" has the lowest value, but only a slight difference. However, it is in first place by a large margin in all other performance sub-criteria. This segment again ranks highest in all the sub-criteria of the "customer cooperation" criterion. While it occupies the midrange in the "production difficulty" sub-criterion under the "customer workload" criterion, the remaining are in the first order with the lowest. While all the sub-criteria under "customer potential" are in the last order, "customer total revenue" ranks in the middle. In general, customers in the third segment can be evaluated as having high performance and cooperation and a medium level of customer difficulty and potential.

The significance level of three segments is calculated using the multiplication of center coordinates and segment weight arrays by considering whether the criteria are positive or negative. Table 4 shows that the most important customer group is that of pearls (third segment), followed by hidden potentials (second segment), and finally guests (first segment).

Table 4  
Segment Profiles

	Number of Customers	Name of Segments	Customer Purchasing Performance	Customer Cooperation	Customer workload	Customer Potential	Segment Score	Significance Level
Segment #1	341	Guests	Low	Low	Moderate	Moderate	.000	3
Segment #2	28	Hidden Potentials	Moderate	Moderate	High	High	.006	2
Segment #3	10	Pearls	High	High	Moderate	Moderate	.044	1

Although "guests" has the highest number of customers, customers in this exhibit category have low purchasing performances and cooperation profiles. Accordingly, the company has too many customers that do business on a small scale. This segment does not include those customers worthy of investment from a business point of view. However, with sufficient resources obtained from this large number of customers, those customers with low levels of customer workload and high levels of customer potential can be selected for strengthened bilateral relations.

The "hidden potentials" group consists of influential customers. However, not enough sales revenue is obtained from these customers. Insufficient cooperation with these customers or customer workload issues could cause this. The company should increase its promotional activities and improve its relations with these high-potential customers. Customer special product requests, difficulties in production, and raw material difficulties also prevent a sufficient level of business from being conducted with these customers the company can invest in these areas by determining the standard production processes and common raw material needs. In this way, the company can increase its business volume and cooperation with "hidden potentials." Moreover, some customers in this segment can be shifted to the "pearls" group over time.

"Pearls" are the company's most valuable customers, with whom it does the most business and with whom the most revenue is generated. Companies should implement retention strategies for these customers utilizing high levels of collaboration and purchasing performance, and long-term relationships should be established. The company can conduct joint studies to increase the regions serving these lucrative and cooperative customers. Thus, the potential and business volume of these valuable customers can be increased.

## Conclusion and Discussion

CRM maximizes customer value and increases competitiveness through information sharing in industrial markets and the integration of processes in the supply chain (Zeng et al., 2003). Customer segmentation, the most prominent function within the scope of analytical CRM, is a method frequently applied by industrial enterprises in relationship management (Xu et al., 2002; Wilson et al., 2002). Grouping customers with common characteristics makes it easier for companies to develop common offers for the customers in the same group. One of the most popular criteria in customer grouping is CLV, which calculates the financial gain a customer can bring to the company throughout the relationship. However, focusing on only monetary value decreases the inclusivity of customer segmentation. To determine different customer types, companies should consider adopting segmentation variables derived from applying a broad perspective according to their managerial decisions.

Although studies in recent years have focused on multi-criteria segmentation models (Güçdemir & Selim, 2015; Sheikh et al., 2019; Kim & Lee, 2023; Barrera et al., 2024), no comprehensive segmentation model for industrial customers has been found to the best of the author's knowledge. This study aimed to develop a comprehensive and multi-criterial customer segmentation model tailored to industrial customers by integrating financial performance, cooperation levels, challenges, and potential growth. Under these four criteria, 17 sub-criteria determined by the in-depth interview method for the industrial enterprise were used to cluster the real data of a case study. By employing the fuzzy C-means clustering method, the model categorized the company's 379 industrial customers into three distinct segments: Pearls, Hidden Potentials, and Guests. The fuzzy AHP method was further applied to determine the importance levels of these segments, providing strategic insights for managerial decision-making (Strahle & Spiro, 1986).

The results reveal that Pearls represent the company's most valuable customers, contributing significantly to its revenue and maintaining strong business relationships. To sustain and enhance these relationships, the company should implement a retention strategy focusing on customer loyalty, personalized services, and long-term collaboration. Establishing tailored loyalty programs, providing exclusive offers, and dedicating key account management resources are recommended actions. On the other hand, Hidden Potentials are characterized by their substantial purchasing power and growth potential, although the company's current relationships with them are underdeveloped. A building strategy should be pursued to strengthen these relationships through targeted promotional activities, joint innovation projects, and

closer engagement. Developing customized product offerings and enhancing service quality can stimulate future business growth. The Guests segment, although consisting of a large number of customers, contributes minimally to the company's financial performance and exhibits low levels of cooperation. Applying harvesting or divesting strategies is advisable for this group. The company could focus on selective retention of the most promising customers within this segment while reducing resource allocation to those with limited potential. Exploring cost-effective service solutions and reassessing contract terms can optimize resource utilization.

The study effectively meets its research objectives by providing a robust, adaptable, and multi-dimensional segmentation model. By identifying and categorizing industrial customers based on financial performance, cooperation levels, workload, and growth potential, the model provides actionable insights that directly support strategic decision-making. It offers insights for businesses seeking to maximize customer value, improve operational efficiency, and strengthen competitive advantage. Additionally, the adaptable nature of the model enables companies to adjust criteria weights in response to changing market conditions. For instance, during periods of economic uncertainty, companies may emphasize financial performance, while in times of market expansion, customer potential may gain greater significance. Future research could apply the model across different industries and customer types. Additionally, longitudinal studies can track customer transitions between segments over time, offering insights into the long-term impacts of strategic decisions.

### **Theoretical/Practical/Economic and social contributions**

This study contributes to the literature on B2B customer segmentation by introducing a holistic, multi-criterial approach that extends beyond traditional financial metrics. Unlike single-criteria models, this study supports the importance of incorporating cooperation, workload, and potential growth dimensions (Marcovic et al., 2020; Virtanen & Björk, 2024; Kreye & van Donk, 2021; Menon et al., 2024; Hanneke et al., 2024). By employing fuzzy C-means and fuzzy AHP methodologies, the study advances theoretical understanding of how qualitative and quantitative factors can be integrated into customer segmentation models. From a managerial perspective, this study offers a clear framework for industrial companies seeking to optimize their CRM strategies. The segmentation model provides actionable insights that guide decision-making processes, enabling companies to allocate resources efficiently and prioritize customer engagement. Managers can implement tailored marketing strategies aligned with segment-specific needs, resulting in increased customer satisfaction and revenue growth. Furthermore, the dynamic nature of the model enables its adaptation to different market conditions and industry-specific requirements (Sota et al., 2018).

The study's holistic segmentation model not only offers theoretical and practical advancements but also provides economic and social benefits. By applying the insights gained from this research, companies can create value for both themselves and their stakeholders, fostering sustainable growth and enhanced competitive positioning. The proposed model supports improved resource allocation by focusing on high-value customers and recognizing growth opportunities. By implementing retention and building strategies for strategic segments, companies can maximize customer lifetime value (CLV) and achieve long-term profitability. Moreover, the efficient allocation of resources reduces operational costs, providing a competitive advantage in industrial markets (Hiziroglu, 2013; Kumar & Philip, 2022). On a societal level, the study promotes collaborative business practices by emphasizing customer cooperation and joint value creation. Companies that engage in strong partnerships with their customers foster knowledge sharing and mutual growth (Mention, 2011; Virtanen & Björk, 2024). Furthermore, supporting customer development through targeted relationship-building efforts can lead to more resilient supply chains and sustainable market ecosystems.

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## Genişletilmiş Özet

### Amaç

Bu çalışma, endüstriyel pazarda müşteri segmentasyonu için finansal performans gibi tek bir bakış açısını ele almanın yetersizliğini vurgulamaktadır. Geleneksel segmentasyon yöntemlerinde müşterilerin ortak profilleri oluşturulurken, çeşitli müşteri özellikleri göz ardı edilmekte ve bu durum homojen gruplar yaratmada yetersiz kalmaktadır. Çalışma, bu eksiklikleri giderebilmek amacıyla çok boyutlu bir segmentasyon modeli geliştirmeyi hedeflemektedir. Önerilen model, dört ana kriteri (müşteri satın alma performansı, müşteri işbirliği, müşteri iş yükü ve müşteri potansiyeli) dikkate alarak, işletmelerin müşterilerini daha kapsamlı bir şekilde analiz etmelerini ve bu doğrultuda daha etkili pazarlama stratejileri ve yönetsel kararlar alabilmelerini sağlamayı amaçlamaktadır. Bu bağlamda, araştırma hem teorik hem de pratik açıdan önemli bir boşluğu doldurmayı hedeflemektedir.

### Tasarım ve yöntem

Bu çalışma uygulamalı bir araştırma olup, endüstriyel müşteri segmentasyonu için dört üst kriter (müşteri satın alma performansı, müşteri işbirliği, müşteri iş yükü ve müşteri potansiyelini) üzerinden çok boyutlu bir segmentasyon modeli önermektedir. Vaka çalışması olarak seçilen işletmenin satış ve pazarlama yöneticisi ile yapılan derinlemesine görüşme yöntemi sonucunda üst kriterler altında 17 alt kriter belirlenmiş ve ikili karşılaştırma matrisleri oluşturulmuştur. Nitel ve nicel bilgilerin işlenmesini kolaylaştırması, hiyerarşik yapıyı uygulaması ve tutarsızlığı azaltması gibi güçlü yönlerinden dolayı kriter ağırlıklarının hesaplamak için Bulanık Analitik Hiyerarşik Süreç (Fuzzy Analytical Hierarchy Process) yönteminden yararlanılmıştır. Segmentasyon yöntemi olarak Excel Visual Basic for Applications üzerinde kodlanan Bulanık C-Ortalamlar Kümeleme Algoritması (Fuzzy C-Means Clustering Algorithm) kullanılmıştır. Bulanık c-ortalamlar yöntemi hiyerarşik olmayan bölümleyici algoritmalarındandır. Her küme elemanının her kümeye olan farklı aitlik dereceleri vardır ve hangi kümeye olan yakınlık derecesi fazla ise o kümenin elemanı olduğu varsayılır. Eğer bir eleman kümesine uyumlu bulunmayıp o kümeden çıkarılmak isteniyorsa ikinci en yakın kümeye bakılabilir. Ayrık elemanların fazla olduğu veri setleri için güçlü özelliklerinden dolayı bu yöntem tercih edilmiştir. Elbow Yöntemi ve Silhouette İndeks Yöntemi sonuçları karşılaştırılarak ideal küme sayısı bulunmuştur. Elbow Yöntemi, optimal küme sayısını bulmak için farklı küme sayılarına sahip en yakın ağırlık merkezi ile her bir veri noktasının Hata Kareler Toplamı (SSE) değerini bularak çalışır. Küme sayısı arttıkça SSE azalır ve SSE'de en fazla düşüşün olduğu belirli bir küme sayısı değerinde dirsek yapar ve bu noktada verilerin bölünmesi durdurulur. Silhouette İndeks Yönteminde ise kümeleme işlemi sonrası her bir veri elemanı için küme içi diğer elemanlarla olan yakınlık ve küme dışı diğer elemanlarla olan yakınlık değerlerinin oranlanması ile hesaplanır. Sonuç değerinin 1'e yakınlığı kümelemenin başarısını gösterir. Bu yöntemler ile 379 adet müşteri belirlenen 17 segmentasyon kriterine bağlı olarak 3 segmente ayrılmıştır. Çalışmada, elde edilen her bir müşteri segmentinin pazarlama stratejilerinin oluşturulmasında ve müşteri ilişkilerinin yönetilmesinde nasıl kullanılabileceği detaylandırılmıştır.

### Bulgular

Araştırma sonucunda, çok boyutlu segmentasyon modelinin B2B müşteri segmentasyonu sürecinde önemli bir fark yaratacağına dair güçlü bulgular elde edilmiştir. İşletme Satış ve Pazarlama Yöneticisi ile derinlemesine görüşmeler sonucunda dört üst kriter altında 17 alt kriter belirlenmiştir. Buna göre müşterilerin satın alma davranışları ve bunun sonucunda getirdiği finansal sonuçları temsil eden "Müşteri Satın Alma Performansı" üst kriteri altında "Brüt Kârlılık", "Satın Alma Miktarı", "Ödeme Vadesi", "Sipariş Sıklığı", "Satış Geliri", ve "İskonto Oranı" alt kriterleri yer almaktadır. Müşterilerin işletmeyle olan ilişkisindeki katkı durumuna bakıldığı "Müşteri İş Birliği" kriterinin altında "Talep Tahmin Uyum Oranı", "Rakipten Çevirdiği Müşteri Oranı", "Ortak ARGE Çalışması" ve "Sadakat Derecesi" alt kriterleri toplanmıştır. Müşterilerin siparişlerine bağlı işletmeye getirdiği yükün göstergesi olarak "Müşteri Zorluğu" kriterinin altında "Hammadde Tedarik Zorluğu", "Üretim Zorluğu" ve "Özel Ürün Talebi" yer

almaktadır. Son olarak müşterinin ilişki süresi ve gelecek satın alma getirisi ile bağ kurulan “Müşteri Potansiyeli” üst kriteri altında “Müşteri Cirosu”, “Portföyündeki Alternatif Marka Sayısı”, “Bulunduğu Bölgedeki Rakip Sayısı”, “Hizmet Ettiği Bölge Sayısı” alt kriterleri belirlenmiştir. Bulanık C-Ortalamalar Kümeleme Algoritması kullanılarak oluşturulan müşteri segmentleri, müşterilerin satın alma davranışları, işbirliği düzeyleri, iş yükleri ve gelecekteki potansiyel iş hacimleri gibi faktörlere göre anlamlı gruplara ayrılmıştır. Sonuçlara göre önem derecesi en yüksek olan “Değerli Müşteriler” işletmenin en çok iş yaptığı ve en fazla gelir elde ettiği en kıymetli müşterileridir. İşletme, iş birliği ve satın alma performansı yüksek bu müşterilerle uzun süreli ve güçlü ilişkiler kurarak elinde tutmalıdır. İkinci önem sırasında yer alan “Potansiyeli Yüksek Müşteriler” segmenti büyük ve güçlü müşterilerden oluşmasına rağmen bu müşterilerle olan iş ilişkileri zayıftır. İşletme, potansiyeli yüksek olan bu müşterilerle olan ilişkilerini güçlendirilmeli, tutundurma faaliyetleri arttırılmalı ve iş hacmini arttırıcı yatırımlarda bulunmalıdır. Son sırada yer alan “Düşük Değerli Müşteriler” segmenti diğer segmentlere göre en fazla müşteri sayısına sahip segment olmasına rağmen satın alma performansı ve iş birliği açısından düşük bir profil çizmektedirler. Buna göre işletmenin çok fazla küçük çapta iş yaptığı müşterisi olduğu sonucu çıkarılmaktadır. Bu müşteriler için pazarlama harcamalarını düşük tutmak işletme açısından uygun olacaktır.

## Sınırlılıklar

Bu çalışmanın sınırlılıkları arasında yalnızca belirli bir endüstriye ait verilerin kullanılmış olması yer almaktadır. Çalışma, 379 müşteri verisini içermekte olup, bu verilerin büyük bir kısmı belirli bir sektörden alınmıştır. Bu nedenle, elde edilen sonuçların diğer sektörlerdeki müşteri segmentasyonu için genellenmesi sınırlı olabilir. Ayrıca, araştırmada kullanılan veri kümesi belirli bir zaman dilimi içinde toplanmıştır. Müşteri davranışları ve pazar koşulları zamanla değişebileceği için, segmentasyon modelinin uzun vadede nasıl bir performans göstereceği konusunda ek araştırmalar yapılması gerekebilir. Diğer bir sınırlılık, segmentasyon modelinin zaman içinde değişen müşteri ihtiyaçlarına ne derece uyum sağlayabileceğidir. Müşteri segmentleri, belirli bir zaman dilimi için geçerli olabilir, ancak işletmelerin sürekli olarak bu segmentleri güncellemeleri ve yenilikçi stratejiler geliştirmeleri gerekebilir.

## Öneriler

Bu çalışma, B2B müşteri segmentasyonuna bütünsel bir yaklaşım sunarak, teorik olarak müşteri segmentasyonunun daha kapsamlı bir şekilde yapılması gerektiğine dair önemli bir katkı sağlamaktadır. Uygulama açısından, işletmelerin müşteri ilişkilerini ve pazarlama stratejilerini daha etkili bir şekilde yönlendirebilmeleri için dört ana kriteri dikkate alarak segmentasyon yapmaları gerektiği önerilmektedir. Bu sayede, müşteri memnuniyeti artırılabilir, işbirliği düzeyleri iyileştirilebilir ve gelecekteki iş hacmi daha doğru bir şekilde tahmin edilebilir. Sosyal açıdan, müşterilerin daha iyi anlaşılması ve ihtiyaçlarının doğru bir şekilde belirlenmesi, müşteri ilişkilerinde şeffaflık ve güveni artırabilir, bu da endüstriyel sektördeki iş yapma kültürünü olumlu yönde etkileyebilir.

## Özgün değer

Bu çalışma, endüstriyel müşteri segmentasyonu konusunda mevcut yaklaşımların ötesine geçerek, çok boyutlu bir model önerisi sunmaktadır. Çalışmanın bulguları, geleneksel segmentasyon yöntemlerine kıyasla, müşterilerin daha fazla özellik ve ihtiyaç bazında segmentlere ayrılmasının işletmelere daha esnek ve etkili bir pazarlama stratejisi geliştirme imkânı sunduğunu göstermektedir. Ayrıca, Bulanık C-Ortalamalar Kümeleme Algoritması ve Bulanık Analitik Hiyerarşik Süreç yöntemlerinin birleştirilmesi, modelin doğruluğunu arttırmış ve sektörel uygulamalar için pratik bir çözüm sunmuştur. Bu özgün yaklaşım, endüstriyel müşteri segmentasyonunda yenilikçi bir bakış açısı oluşturmuş ve alanındaki literatüre katkı sağlamayı amaçlamıştır.